COMBINING THE SURVEILLANCE OF UNMANNED AERIAL VEHICLE AND DEEP LEARNING METHODS IN SAGO PALM DETECTION

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Abstract
The study concerns on the detection of sago palm tree based on Unmanned Aerial Vehicle (UAV) images. Sago palm (Metroxylon Sagu Rottb) lives ecologically in Indonesia, particularly in Papua and Papua Barat. However, our previous study in Papua, especially in Merauke Regency convinced us that 12 of 20 regions tend to lose the potential area of sago palm. To support the detection process from higher spatial data resolution of UAV, we applied a deep learning model based on Convolutional Neural Network (CNN). Although existing studies have implemented a deep learning model based on CNN, rare immersion has been delivered by using deep learning networks, such as mobile net V2 in sago palm detection. Therefore, this study aims to detect sago palms from UAV imagery, and to examine the performance of mobile net V2 in detection tasks. As a result, the metric performance demonstrates good potential as a classifier and predictor.. To add this, as shown by the independent t-test of sago trees (58.3±6.8%) compared to other vegetations (27.4±13,4%) ($p<0.001$), prompting to become more rigid in sago palm detection.

Key words: *sago; classification; UAV; mobile net V2.*

INTRODUCTION

Sago palm was affiliated with palmae family known as Metroxylon Sagu Rottb., grows in swamps or salty areas of tropic lowlands in South East Asia, particularly in Thailand, Malaysia, Papua New Guinea, and about 85% of world's sago area is in Indonesia (*Hidayat et al., 2018; Lim et al., 2019*) , specifically in Papua, and Maluku (*Sidiq et al., 2021*). The potential use of sago were introduced these days, especially the primary product of sago palm which is sago starch. Numerous earlier studies have found that the primary product of this palm, which is sago starch, used as a food substance in traditional cakes, or as a raw material for agro industry, and others aspect of sago can be refer to (*Karim et al., 2008*). Sago pith waste (SPW) or 'Sago hampas' can be used for Bio-ethanol production (*Thangavelu et al., 2014*). Other product of Sago palm determined by study of fermentable sugars from enzymatic hydrolysis of sago pith residues were transformed to acetone-butanol-ethanol (*Linggang et al., 2013*). In Papua, sago plays an important role as a staple food and also a part of indigenous costumes (*Sidiq et al., 2021*), thus, sago waste is used as livestock feed or as bio-energy alternative (*Jonatan et al., 2017*). However, our previous study found that the potential habitat of sago palm in the area of Merauke Regency of Papua Province of Indonesia was decreased, twelve of twenty regions of the area tend to lose over time. On the other hand, other sectors such as the settlement areas, and agricultural regions were significantly increased during 29 years of study (*Letsoin et al., 2020, 2022*). Therefore, our current study focuses on the detection of sago palm trees in the selected area. During the last decades, various approaches have been investigated and applied for palm detection purposes, for instance, airborne and ground-based multispectral data combined with spatial and spectral information. Thus, different algorithm classifiers such as image processing methods, machine learning and deep learning methods have applied. Classical image processing methods consists of, for example, template matching, image binarization. Furthermore, machine learning that contains of two general ways, likewise feature extraction by using HOG; and classifier prediction by using Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), etc. Today, several studies elaborated deep learning by semantic segmentation, object detection and Convolutional Neural Network (CNN). CNN architectures are now extensively developed in various studies, such as AlexNet, ResNet, Inception or mobile net (*Hidayat et al., 2018; Zheng et al., 2021*). Hence, our study concerns on the detection of sago palm by applying mobile net V2 as a classifier, in addition, to assess the characteristic of the classifier in discovering sago palm area and other vegetation based on metric performance as well as analyzed statistically.

MATERIALS AND METHODS

The specific multirotor platform is accustomed as unmanned device to capture images over the sago fieldwork within the specification as follows; Autel Robotics version 2 (EVO II Pro 6K), equipped with advance camera of 12 computer vision sensors, thus, two sonar sensors, two LED landing lights. This drone product also consisting of ultra-HD with a 1-inch sensor, supports range of f2.8 to f11, also JPEG/RAW format of data types with a resolution of 5472 x 3648 pixel. The Autel drone flights flew over the sago field area of a double grid via 70% and 80% of forwarding overlap, 70% and 60% of side overlap, with 60.3 m of altitude. The drone systems have integrated with mission flight planner around the area of 74.600 m^2.

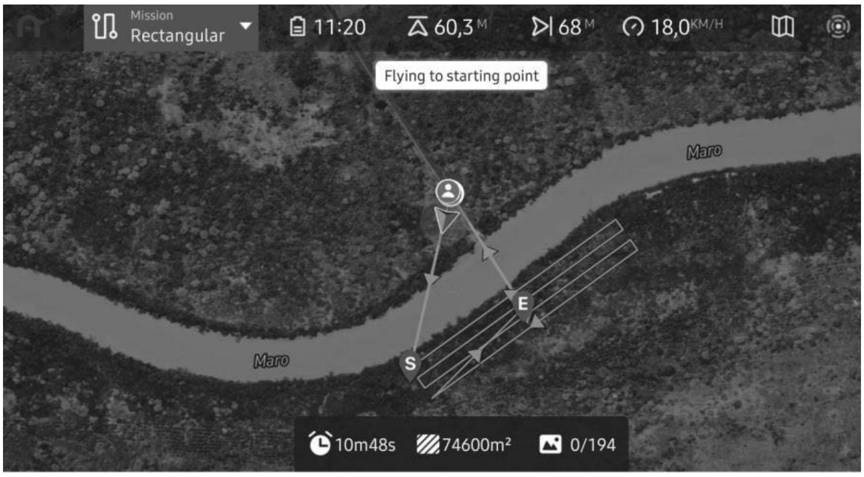

Fig. 1 Mission flight planner

The study area is in Merauke Regency, Papua Province of Indonesia which is positioned between Mappi Regency and Boven Digoel Regency at the North, the Arafuru Ocean at the South and West, and Papua New Guinea to the East. This regency is considered as the Easternmost city in Indonesia that consists of 20 districts. Merauke Regency also known as the largest area of paddy field approximately 91% over Papua Province of Indonesia. Within the area of 46.074.63 km^2/sq.km, the Regency becomes the largest area around Papua Province. Due to the temperature humidity and air temperature about 80.5% and 2.40-32.06 °C respectively; are generally preferred for paddy field and maize, different vegetables, and plantation crops, for example mustard green, and coconut tree. The Regency also recognized as the three largest maize producers after Nabire Regency and Biak Numfor Regency (*BPS, 2015*). Considering the sago palm habitat in our field work is typically around primary dryland, secondary dryland, primary swamp forest, secondary swamp forest, bush/shrub, grassland, swamp shrub, and swamp area (*Letsoin et al., 2020*), as captured in this study, natural sago forest in this area is lives together with other vegetation along the river and swamp area (Fig. 3).

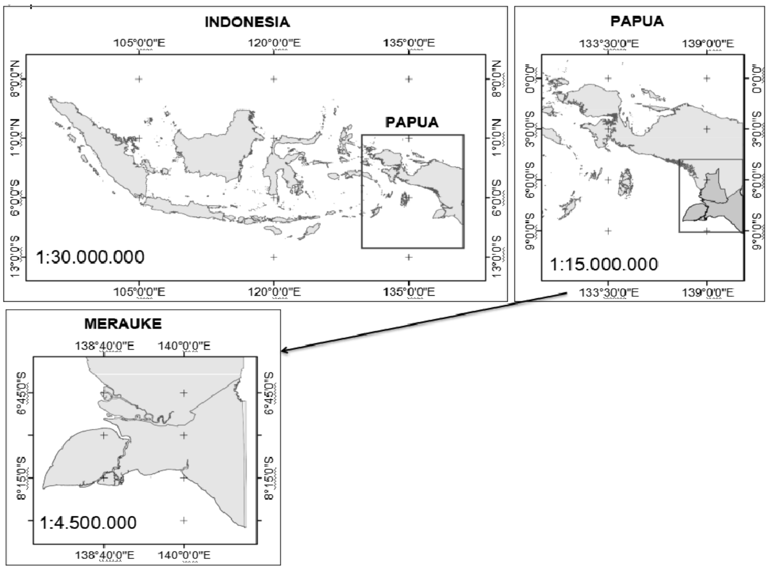

Fig. 2 Study area positioned in Merauke Regency of Papua Province of Indonesia
(137°38'52.9692"E - 141°0'13.3233"E and 6°27'50.1456"S - 9°10'1.2253"S)

The proposed methods to define sago areas from the acquired spectral imagery; consists of three stages, I.e., (1) pre-processing, (2) dataset preparation that contains of data train and data test, and (3) deep learning-based CNN classification. In pre-processing stage, all the images are downloaded from UAV to computer data storage, then all the images are assessed geometrically by using pix4dmapper software. The purpose of the stage is to generate a mosaic of all acquired images to prepare them ready and accurately read as dataset of deep learning model. A classification based on CNN architecture model were designed to detect sago palm area and not sago palm area; for this purpose, mobile net v2 was applied. After the data pre-processing step, all data images were labelled, re sized, and augmented by using MATLAB software. The most common augmentation contains of rotation, cropping, zooming, and flipping. Further, the dataset was divided into two groups namely data train and data test that obtained from the previous step. To train the models, we collect 114 images of sago palm area and other vegetation.

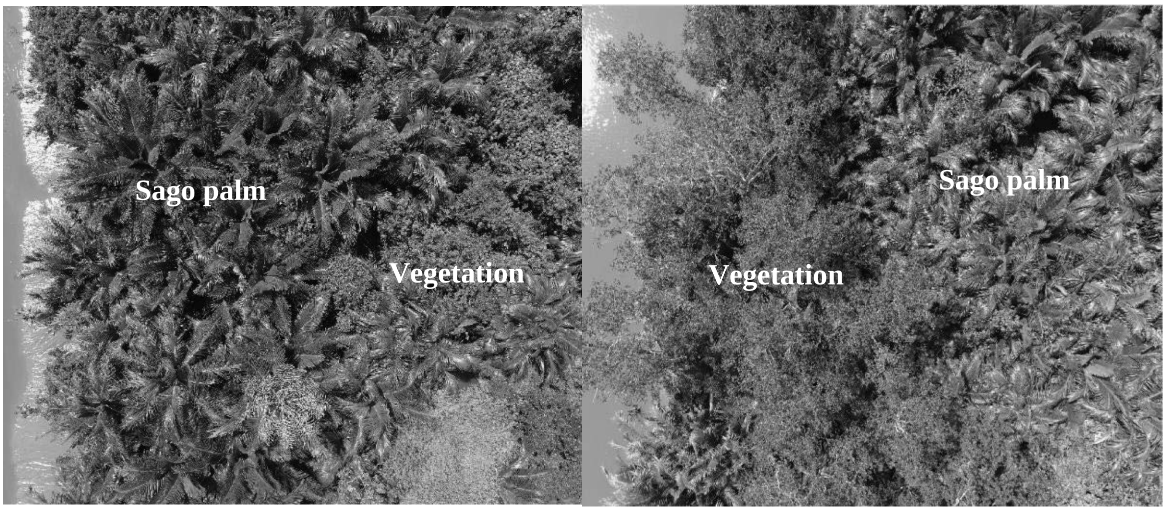

Fig. 3 Sago Forest in Merauke Regency of Papua Province of Indonesia

In accordance with the requirements of the Mobile Net V2 model, the size of input images is adjusted to 224x224. The architecture of Mobile Net V2 mainly consists of two blocks namely linear bottleneck and inverted residual. Conv2d is standard convolution, then avgpool is the average pooling, *c* is the number of output channels and *n* is restated times. Mobile Net V2 has a total layer of 19 residual bottleneck layers, the middle layer used to feature extraction while the last layer is served for classification.

Tab. 1 Network structure of Mobile Net V2

Input	Operator type	T	C	N	S
224 x 224 x 3	Conv2d	-	32	1	2
112 x 112 x 32	Bottleneck	1	16	1	1
112 x 112 x 16	Bottleneck	6	24	2	2
56 x 56 x 24	Bottleneck	6	32	3	2
28 x 28 x 32	Bottleneck	6	64	4	2
14 x 14 x 64	Bottleneck	6	96	3	1
14 x 14 x 96	Bottleneck	6	160	3	2
7 x 7 x 160	Bottleneck	6	321	1	1
7 x 7 x 320	Conv2d 1x1	-	1280	1	1
7 x 7 x 1280	Avgpool 7x7	-	-	1	-
1 x 1 x 1280	Conv 1x1	-	k	-	-

Regenerating characteristics from *N* to *M* channels, with stride *s* and expansion factor *t*. The bottleneck attaches a 1x1 convolution layer in front of the depth-wise convolutional layer and applies linear activation after the pointwise convolutional layer, also obtains the aim of down sampling by designing the parameter *s* in the depth-wise convolutional layer (*Goceri, 2021; Phan et al., 2020; Sandler et al., 2018*).

Tab. 2 Bottleneck structure of Mobile Net V2

Input	Operator	Output
H x W x N	1x1 Conv2d, ReLU	H x W x tN
H x W x tN	3x3 dwise s = *s*, ReLU	H/s x W/s x tN
H/s x W/s x tN	Linear 1x1 conv2d	H/s x W/s x M

to examine the performance of deep learning model, we applied metrics evaluation specifically to evaluate the accuracy of the model on data set. The accuracy is estimated as (*Chen et al., 2021*):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$F1\ score\ = \frac{2 \times (Sensitivity \times Precision)}{Sensitivity + Precision} \quad (2)$$

Whereas TP, TN, FP, FN, represents the number of true positives, true negatives, false positives and false negatives. The number of images predicted to be correct or positive and the number of samples predicted negative were both calculated. To add this, percentage of correctly identified (true positive) sago trees was compared to the proportion of false positive and analyzed statistically using the independent t-test. The p-value >0.05 was determined as a statistical significance difference between variables. Statistical analysis was performed using the IBM SPSS software version 26.

RESULTS AND DISCUSSION

Based on equations (1) and (2), measured data are presented in Table 3, it represents the precision of the model distinguishing the object.

Tab. 3 Metric evaluation

Image Input	Sensitivity	Precision	F1-Score
Sago	0,72	0,72	0,72
Vegetation	0,68	0,68	0,68

Generally, the model was able to identify the object whether sago palm or other vegetation. However, considering the training accuracy of the model which is 97%, and 19 mins of time training; the metric performance was expected to be higher than 0.72. Nonetheless, optimized parameters, mobile net V2 network layer designed in this study, and training time, are needed to be considered. Mobile Net V2 has utilized in classification or detection matters, specifically in embedded platform or mobile devices. To increase the efficiency and time cost this model was enabled to be integrated with other deep learning method such as Faster R-CNN or Long Short-Term Memory (LSTM) (*Hartanto & Wibowo, 2020; Srinivasu et al., 2021*). Comparing the network layer designed, particularly last stage used in this study i, e., after bottleneck residual block and depth-wise convolution, then, global pooling average. Followed by fully connected layer, thus, logits SoftMax and at the final layer is classification output. Nevertheless, adding other deep learning model or techniques between the convolution layer and global pooling average layer could be enhanced the identification result as done by (*Chen et al., 2021*). The training performance for ten epochs as follows: training accuracy, test accuracy, training loss of 98,31%, 91,07, 1,3224 respectively. Also, both F1 score, and sensitivity was around 89%, however, as shown by table 3, the performance result of the mobile network V2 is about17% lower than the earlier study. In addition, the training validation, training loss in this study was 97.05%, 0,20% subsequently. On one hand, attaching a shape detector as output, for example box regressor, is helpful to identify the object properly (*Hartanto & Wibowo, 2020*). Although based on our statistical analysed, the results presented a significantly higher proportion of the machine correctly identifying sago trees (58.3±6.8%) compared to other vegetations (27.4±13,4%) ($p<0.001$, Independent t-test). Nevertheless, integrating the mobile network layer as used in this study within other deep learning techniques, and fine-tuned parameters such as epoch, learning rate, L2 regulation, and validation frequency are required in our future work.

CONCLUSIONS

The study has utilized mobile network V2 in sago palm detection based on an UAV RGB imagery. According to the experiments with seven epochs, initial learn rate and L2 regulation = 0.0001, the data training accuracy is 97%. Although, the metric performance was not significantly higher compared to several earlier studies, the statistical analyzed has shown the model is quite representative in classifying the sago palm or vegetation. As further work to our research, we would like to improve the current result by integrating the network layer designed with other deep learning techniques.

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